# PREDICTING THE BILLBOARD TOP 100: APPLYING MACHINE LEARNING TO MUSIC STREAMING DATA

**DSC288R Group 2**

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# AGENDA

- Background
- Literature Survey
- Why Machine Learning
- Dataset Pipeline
- Feature Extraction
- Details on Models Used
- Results and Observations
- Next Steps and Risks
- References

# BACKGROUND

## Objective of Our Research:

- Predict whether a song has reached the Billboard Top 100 based exclusively on its audio features

## Value to the Music Industry:

- Tailoring music to audience preferences
- Investment in music rights
- Understanding trends

# LITERATURE SURVEY

## Related research fields:

- Music Information Retrieval (MIR)
- Hit Song Science (HSS)

## What people tried to solve this problem:

- Logistic Regression model
- Decision trees
- Random Forest
- K-Nearest Neighbor
- Support vector machines
- Neural networks

# LITERATURE SURVEY (CONT.)

Takeaways from Literature Surveys:

- Importance of data quality
- Models capable of capturing non-linear patterns (i.e. tree-based, neural nets) are more successful

Gaps to address:

- Time-series trends in hit song audio feature composition
- Analysis of feature importance in determining hit song prediction

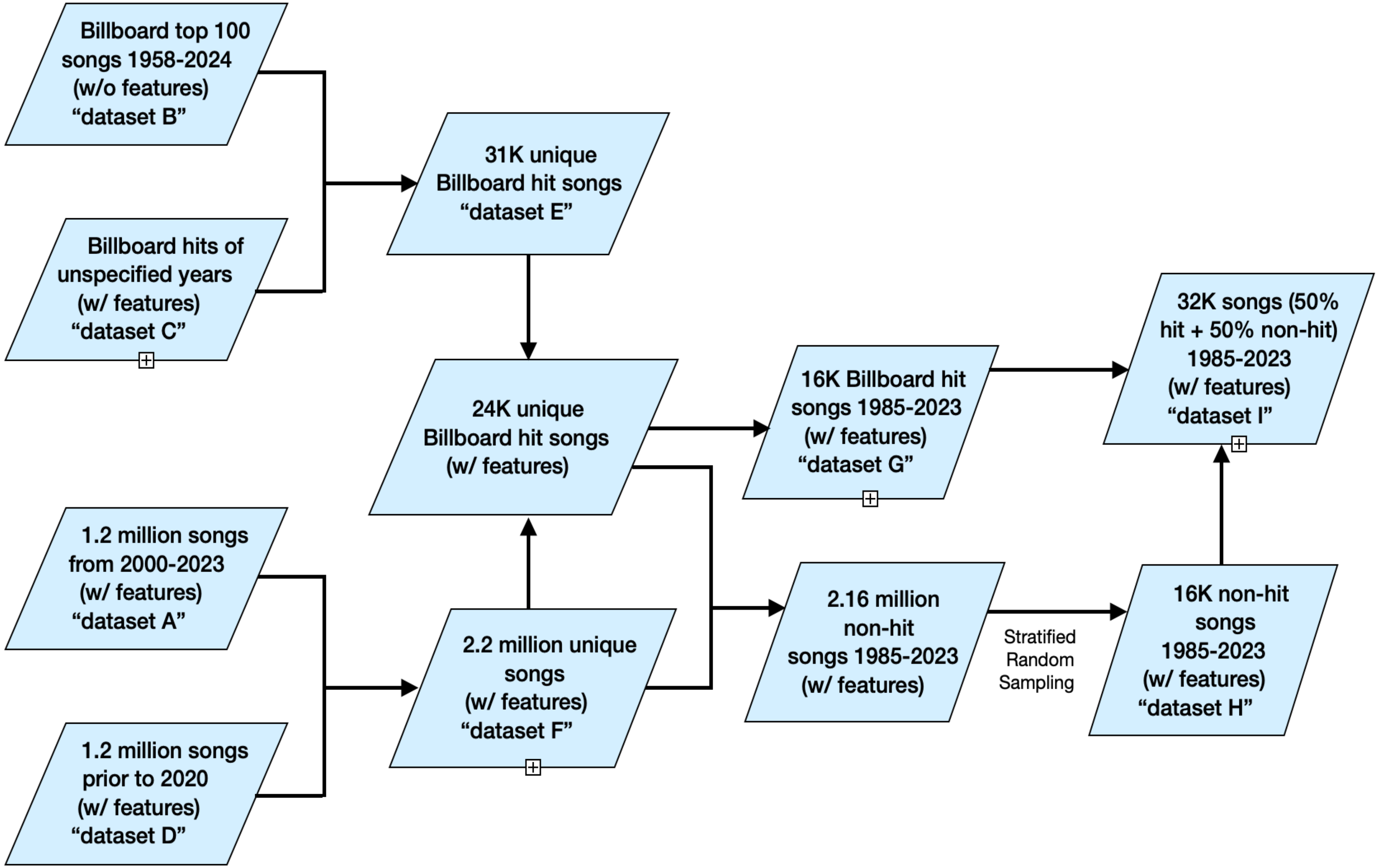
# WHY MACHINE LEARNING

- Machine Learning (ML) algorithms can identify complex patterns in large datasets.
- Song features can be numerous, subtle, and even abstract, such as "danceability" or "energy".

# DATASET PIPELINE

Source Data:

1. Source of truth for Billboard Top 100
2. Billboard data w/ audio features
3. 1.2M songs w/ audio features
4. 1M songs w/ audio features



# DATASET OVERVIEW (CONT.)

16,242 hit songs w/ features

(1985-2023)

+

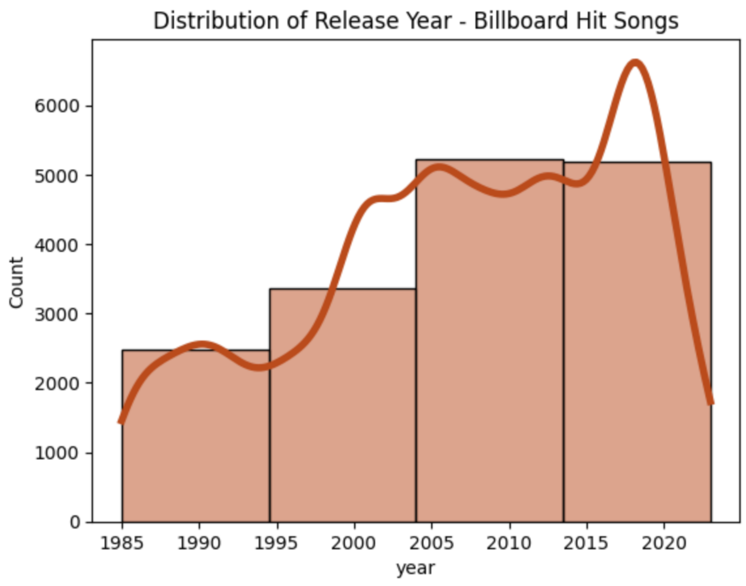
16,242 non-hit songs w/ features

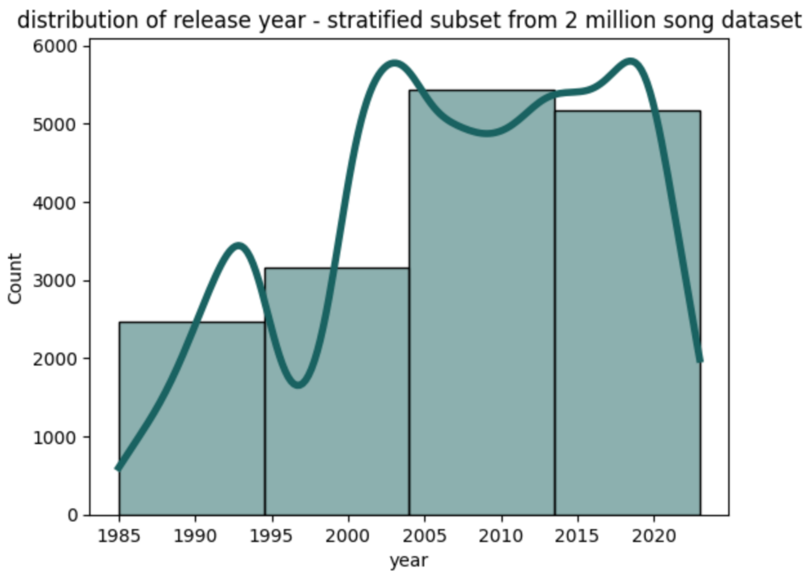
(1985-2023)

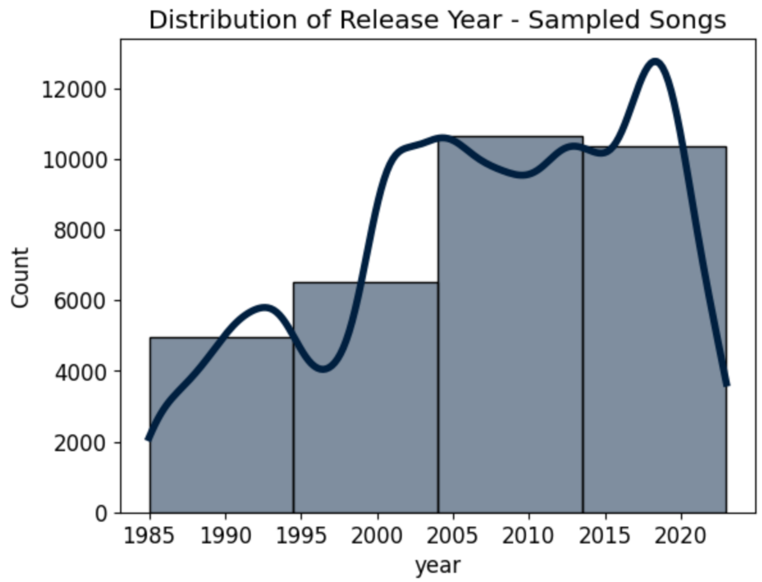
=

32,484 songs w/ features

(1985-2023)



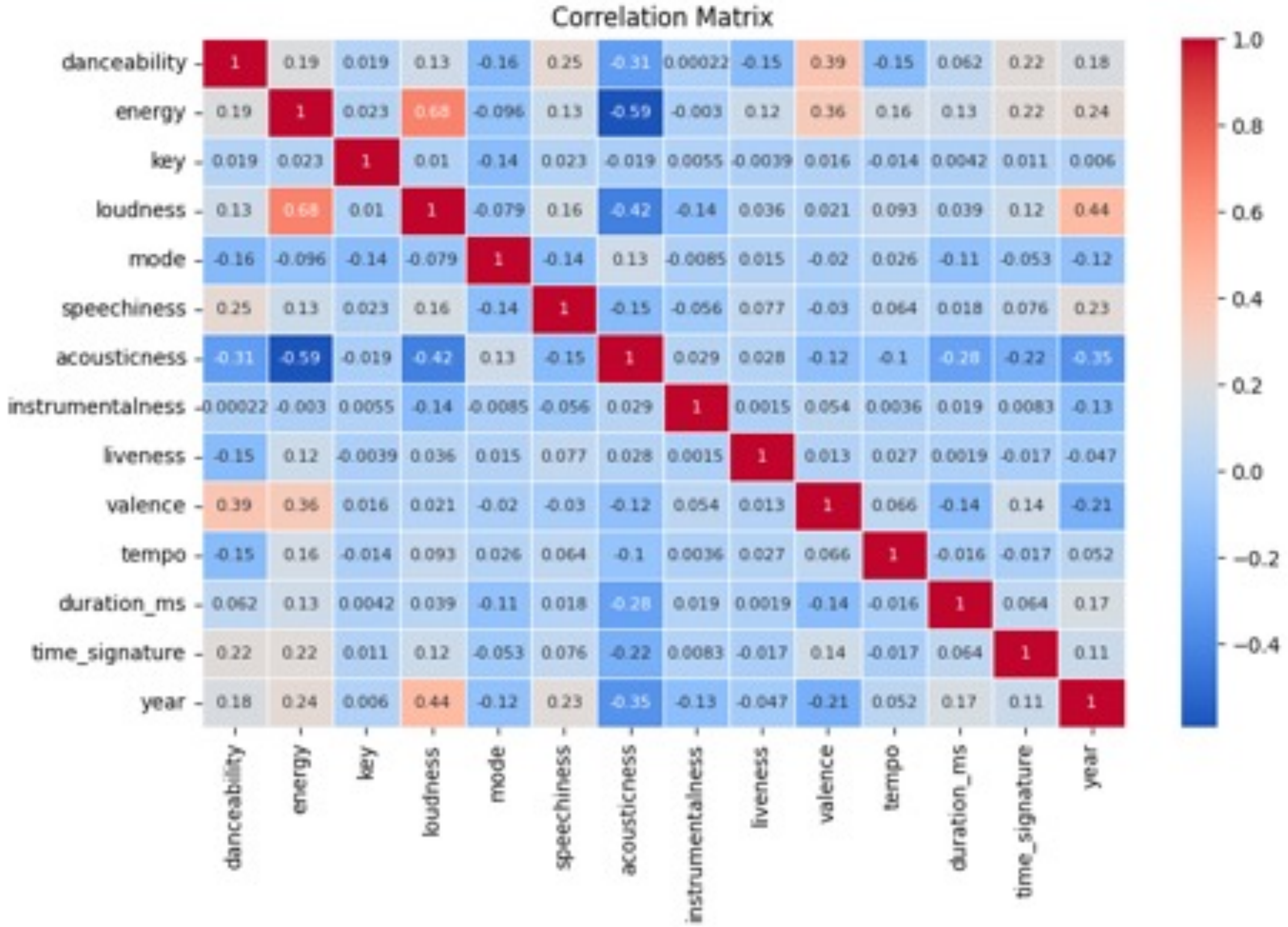



# FEATURE EXTRACTION AND EDA

Correlation of the Features:

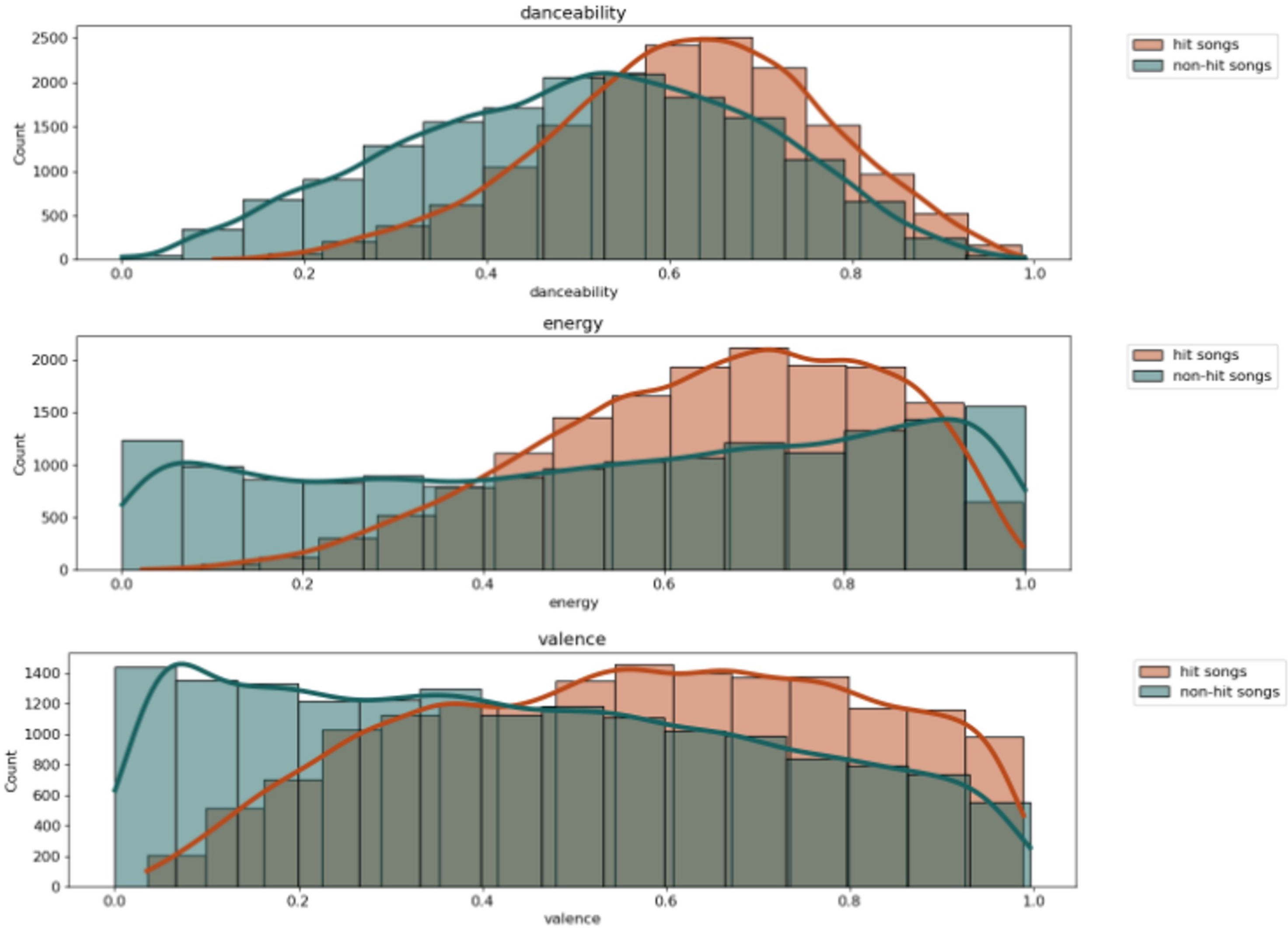
- **Energy** and **Loudness** are highly positively correlated
- **Acousticness** is negatively correlated with Energy and loudness



# FEATURE EXTRACTION AND EDA

High Priority Features:

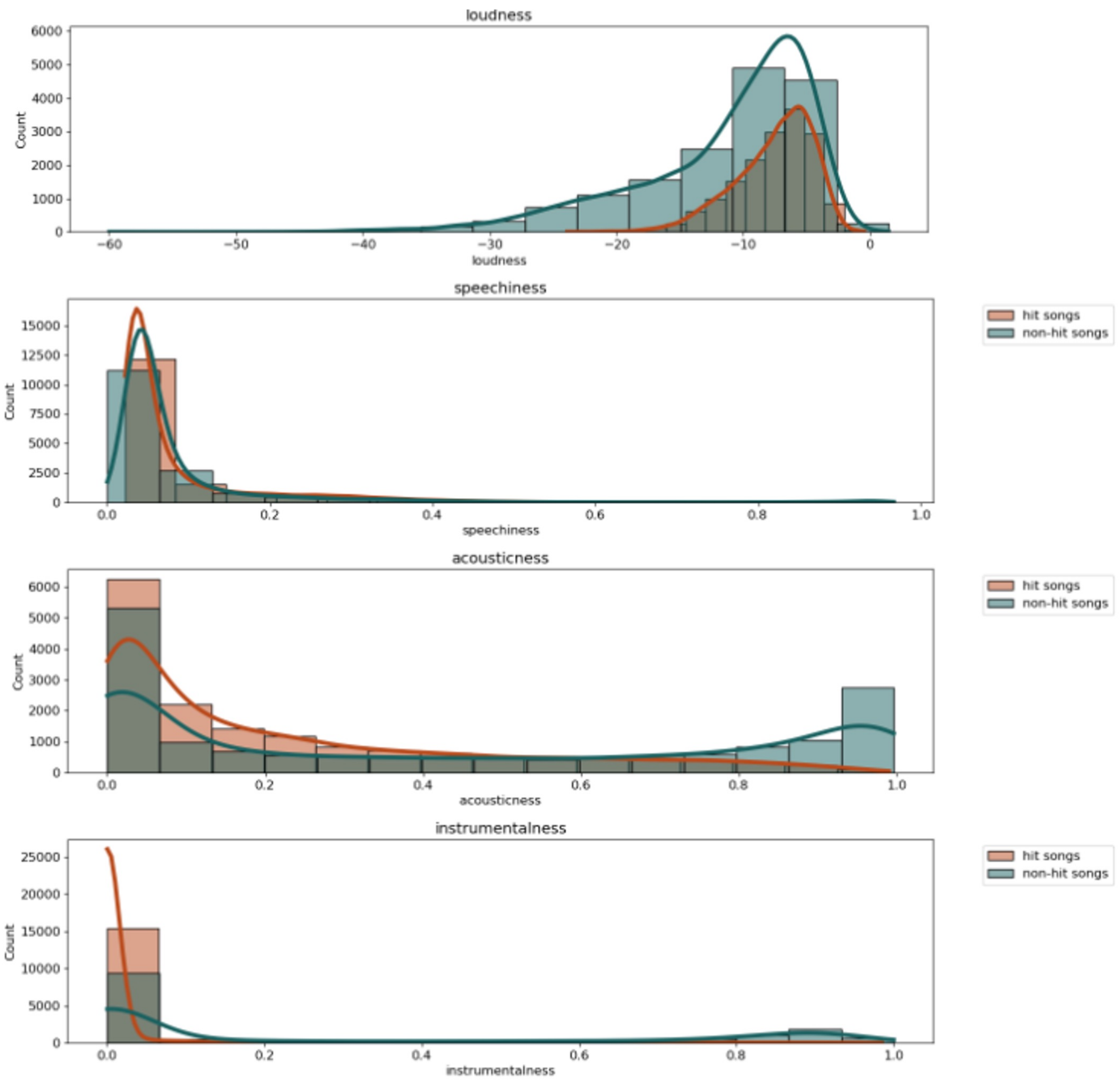
- **Danceability** - Top 100 slight peak shift to the right, differentiated trend from non-hits
- **Energy** - Top 100 larger peak shifted right while non-hits are more evenly distributed
- **Valence** - Top 100 and non-hits essentially have opposite distributions/peaks with hit songs trending to the right. There is a lot of overlap here though



# FEATURE EXTRACTION AND EDA (CONT.)

Mid-Priority Features:

- **Loudness** - Top 100 much tighter range compared to non-hits, not primary focus but could be good addition
- **Speechiness** - Top 100 is very tight lower range, non-hits also skew lower but have a bit more distribution, not primary focus but could be good add-on feature
- **Acousticness** - non-hits have strong peak towards upper range
- **Instrumentalness** - Top 100 all at low end, literally no variation. non-hits also favor low end but has an overall wider distribution of values



# DETAILS ON MODELS USED

## Logistic Regression (LR)

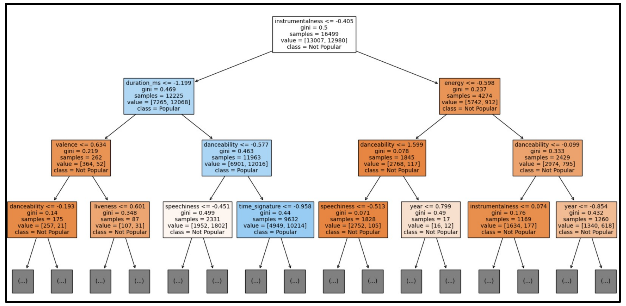
- LR model training:
  - *Used all the features in the dataset*
- Extracted the coefficients of each feature*
- Feature concentration check:
  - *Retrained the model using the 5 features with the highest absolute values of coefficients*

| | Feature | Coefficient | Absolute_Coefficient |
|---|---|---|---|
| 7 | instrumentalness | -1.189548 | 1.189548 |
| 3 | loudness | 0.763486 | 0.763486 |
| 1 | energy | -0.512679 | 0.512679 |
| 6 | acousticness | -0.427913 | 0.427913 |
| 0 | danceability | 0.381690 | 0.381690 |

* Top 5 features w/ the *highest absolute values of coefficients*

## Random Forest (RF)

- RF model training:
  - *Used all the features in the dataset*
- Single decision tree plot**
- Feature importance check
- Hyperparameter tuning:
  - *Randomized Search with Cross-Validation*

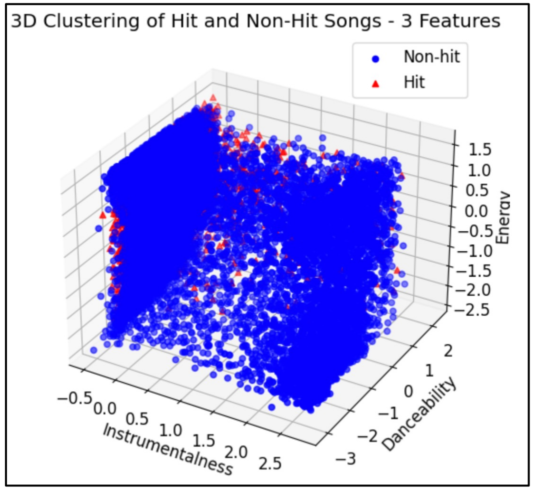



** One single decision tree

# DETAILS ON MODELS USED (CONT.)

## K-Nearest Neighbors (KNN)

- KNN model training:
  - *Used all the features in the dataset*
- 3D clustering of hit and non-hit songs*
  - *Selected three features w/ high importance and low collinearity*




* 3D clustering of hit and non-hit songs

## XGBoost

- XGBoost model training:
  - *Used all the features in the dataset*
- Hyperparameter tuning**:
  - *Randomized Search with Cross-Validation*
- Feature importance check

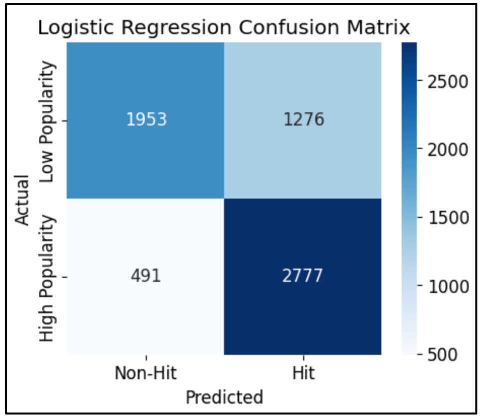
```
Fitting 3 folds for each of 8 candidates, totalling 24 fits
▸ RandomizedSearchCV
▸ estimator: XGBClassifier
    ▸ XGBClassifier
```

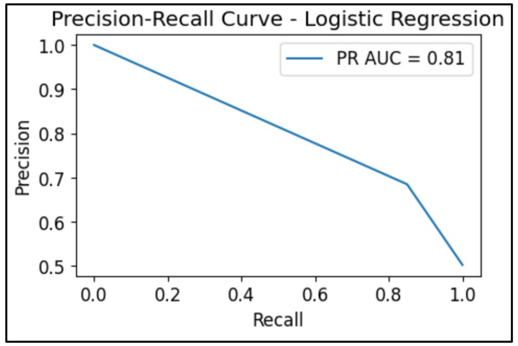
** Hyperparameter tuning using RandomizedSearchCV

# RESULTS AND OBSERVATIONS

## Logistic Regression (LR)

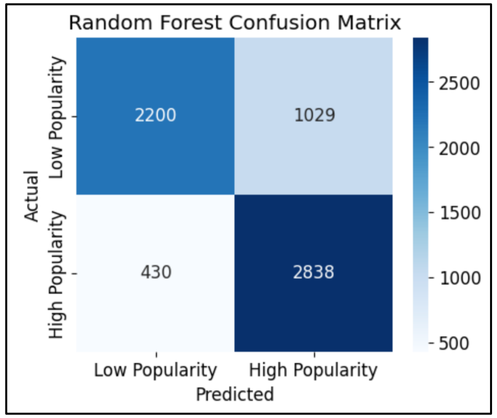
- Accuracy
  - *Initial model: ~ 72.74%*
  - *Retrained model: ~ 71.60%*
- Performance of initial model
  - *Confusion Matrix*
  - *Precision and Recall*

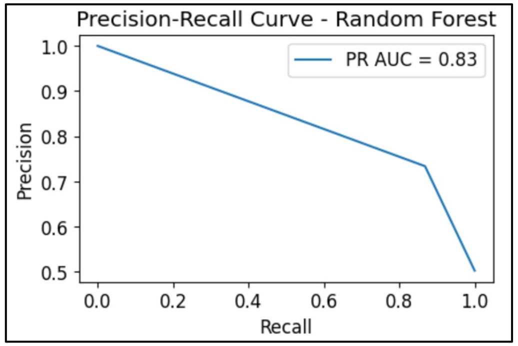



## Random Forest (RF)

- Accuracy
  - *Initial model: ~ 77.16%*
  - *Optimized model: ~ 77.25%*
- Performance of *optimized* model
  - *Confusion Matrix*
  - *Precision and Recall*

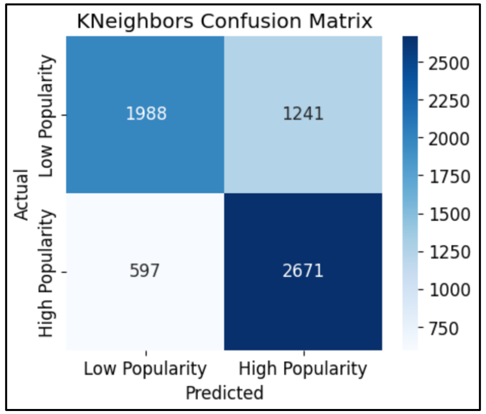


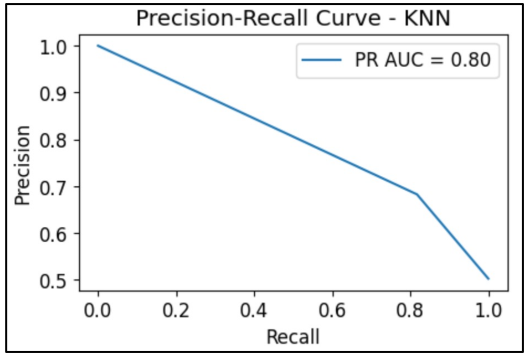



# RESULTS AND OBSERVATIONS (CONT.)

## K-Nearest Neighbors (KNN)

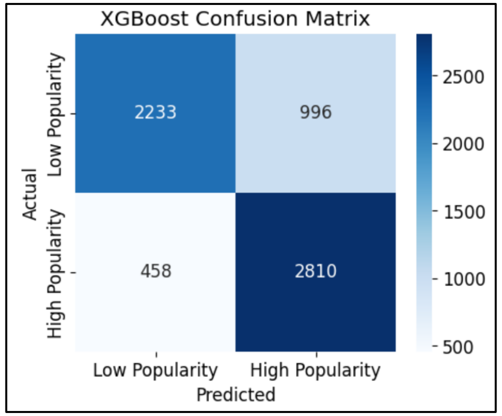
- Accuracy
  - *~ 72.52%*
- Performance
  - *Confusion Matrix*
  - *Precision and Recall*

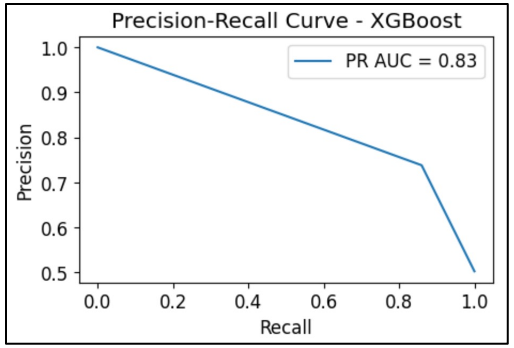



## XGBoost

- Accuracy
  - *Initial model: ~ 77.17%*
  - *Optimized model: ~ 78.08% (Highest)*
- Performance of *optimized* model
  - *Confusion Matrix*
  - *Precision and Recall*
  - *Learning Curve Plot (see slide 16)*

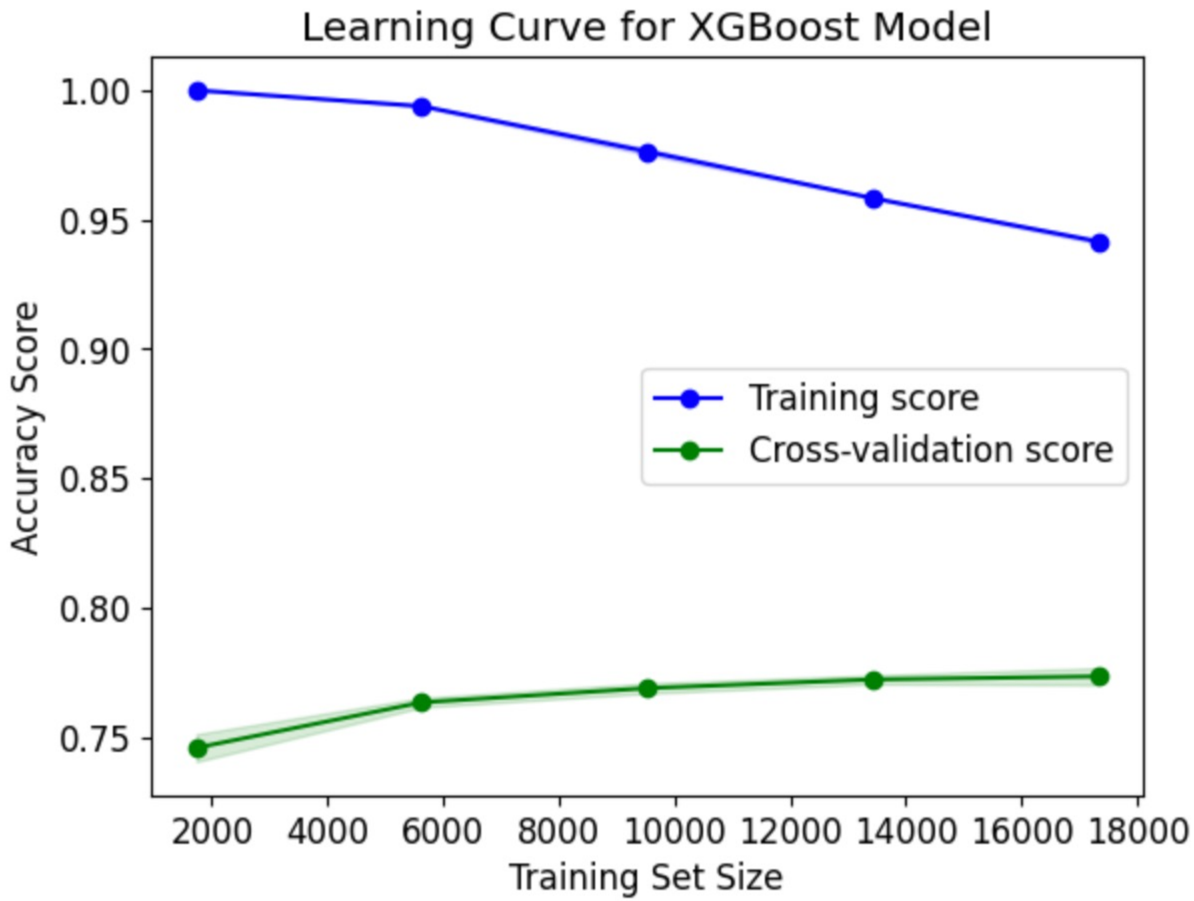


# RESULTS AND OBSERVATIONS (CONT.)

**Learning Curve of the Optimized XGBoost Model**

- Limitation:
  - *A complex model requires a larger amount of data to start generalizing well.*
  - *The training score and the cross-validation score have a trend to converge if more training data is available, which indicates the model may generalize better with a larger dataset.*



# NEXT STEPS AND RISKS

Try other models

- Neural Networks
- Unsupervised clustering for feature engineering

Risks:

- Model overfitting
- Computational efficiency

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